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Distance driven and driving speed when forwarding during final felling in Central Sweden

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Abstract: Factors affecting forwarding work are interesting because they can be used to better optimize forwarding routes and to predict costs. The main objective of this study was to investigate the association between driving speed and driving distance when forwarding. Data was automatically collected during 2.5 years from two large forwarders operating during final felling in central Sweden. Driving speeds for the work tasks Driving unloaded, Loading drive and Driving loaded were analysed using correlation, least-squares regression, and quantile regression. The results showed that speed and distance were strongly correlated for the work element Driving unloaded, while the correlation was weaker for Loading drive and Driving loaded. Possible factors leading to these results are as follows: longer travelling distances stimulate better planning and the establishment of better extraction roads; operators may feel stressed and drive faster as travelling distance increases; and finally, the relative influence of accelerations and decelerations decreases with increasing driving distance. Also, the use of quantile regression was successful and provided information that normal least-squares regression does not provide.

Keywords: cut-to-length; quantile regression; automatic data collection; forwarder; logging; big data

Correct estimations of forwarder driving speed are important when calculating the cost and productivity of machines, machine systems and even when evaluating new working methods (Sundberg, Silversides 1988), and also when trying to optimise forwarding routes (Carlsson et al. 1998; Flisberg et al. 2007; Väätäinen et al. 2012; Ylimäki et al. 2012). Most studies of forwarding and factors that affect the driving speed have focused on load size and different ground conditions like inclination, snow conditions, roughness and bearing capacity (Tufts 1997; Akay et al. 2004; Nurminen et al. 2006), while other factors have been studied only to a limited extent. Some theoretical estimations have been based only on driving distances without any assumptions of terrain parameters (e.g. Belbo, Talbot 2014). However, some previous studies have found and quantified an association between mean driving distance and average speed at the inter-stand level (Kuitto et al. 1994; Väkevä et al. 2001). Several studies indicate that the distance driven has an influence on driving speed at the load level (Nurminen et al. 2006; Ghaffarian et al. 2007; Kumazawa et al. 2011), but these studies did not quantify the association.

Rather than being a direct effect, the association between distance driven and driving speed could be a confounding of distance and other factors to some extent. Ghaffarian et al. (2007) found an increased driving speed at longer distances based on 40 loads, and concluded that this higher speed at longer distances was caused by steeper slopes since forward-

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ing was conducted downhill. According to a deductive study by Gullberg (1997), driving speed during loading increases with increasing distance driven between piles. Gullberg (1997) also deduced that driving loaded and unloaded could be divided into driving on strip roads and driving on haul roads with notably higher driving speed on haul roads. Consequently, it has been concluded that the association between driven distance and driving speed could be caused by a larger proportion of driving on haul roads with higher driving speeds, resulting in higher average driving speeds (Berg, Manner 2018). This cause would be similar to what has been observed for roundwood trucks (e.g. Ranta 2002). Indeed, Kumazawa et al. (2011) found that both load size and average driving speed increase with increasing distance for mini forwarders (2–2.5 t load size) in Japan. However, these authors concluded that this higher speed was mainly caused by the mental stress that longer forwarding distances and lower productivities put on the operators. In Japan, strip roads are pre-made by an excavator and are of good quality (because of steep terrain and concerns about the compaction of volcanic soils), which generally means that there is not any effect of better road conditions on the driving speed. Likewise, Nurminen et al. (2006) observed increasing driving speed at longer distances based on 27 loads from both thinning and final felling stands, and concluded that the proportion of acceleration and deceleration time is higher for shorter distances.

Because it has traditionally been very resource intensive to collect large follow-up datasets of forwarder driving speed and distance, any possible association between driving speed and distance driven has previously been difficult to investigate at the load level. However, the recent developments in on-board computers and software has enabled new ways to study forwarding (e.g. Manner et al. 2016). This development also enables a more in-depth study of the relationship between forwarder driving speed and a given distance driven during a specific work element. The development also enables investigations without affecting the operator's behaviour during the data gathering (i.e. reducing the so-called observer effect). Moreover, it is now also possible to investigate the variation in average driving speed and/or distance-dependent driving speeds (i.e. variable driving speed), which could be interesting during theoretical analyses.

In forest operations studies, confidence and prediction intervals are often difficult to assess because least-squares regression functions must sometimes have the dependent variable logarithmically transformed to achieve normally distributed residuals. This limitation can be remedied using quantile regression which directly models the development percentiles in a similar manner to least-squares regression (Cade, Noon 2003). Quantile regression was originally developed for econometrics but it has also been used in ecological studies and has proven capable of detecting dependences that normal least-squares regression cannot detect. The advantages of quantile regression include the following: it can handle unequal variation when investigating prediction and confidence intervals; it does not lose data when back-transforming the dependent variables; and it models limiting factors. When using quantile regression, it is important to investigate several percentiles as the coefficients can change quite rapidly (Cade, Noon 2003). Thus, quantile regression could most likely be useful also in forest operations studies. However, to our knowledge, quantile regression has previously been used only once in connection with forest machine data (Lu et al. 2017), and that study was aimed at estimating tree characteristics from harvester data.

Objectives

The objectives of this study were to investigate: (1) the association between driving speed and drive distance when forwarding; and (2) if quantile regression could provide added value when investigating automatically collected data from forwarders.

MATERIAL AND METHODS

The time study dataset of Manner et al. (2016) was used. The dataset was gathered between March 2011 and October 2013 from two large forwarders in central Sweden (Fig. 1). The dataset was collected by TimberLink software installed in the on-board computers of two JD 1910E forwarders (22 tonnes with 19-tonne payload capacity) while being operated by nine operators in total [see the original article of Manner et al. (2016) for more detailed descriptions like forest conditions and assortment details]. The number of assortments was not included in our analysis since it does not affect driving speed (Manner et al. 2013).

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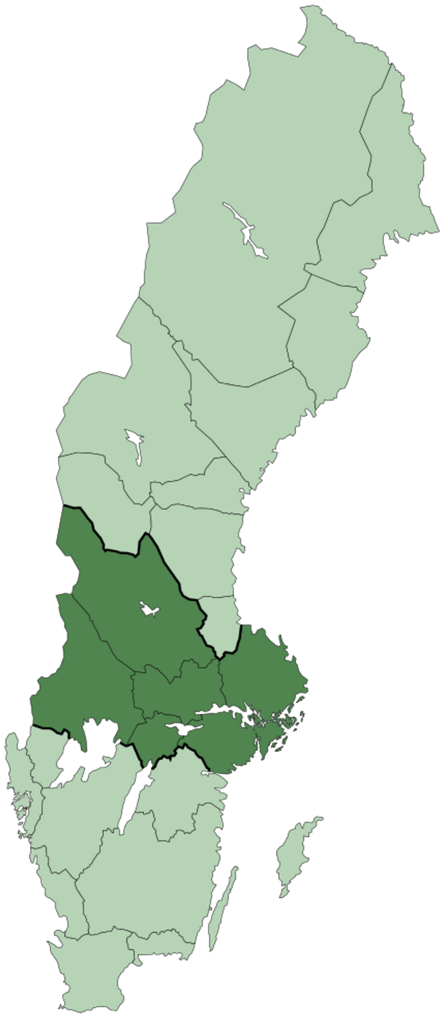

Fig. 1. Data collection region. Dark area shows the location of central Sweden. Map by Lapplänning [CC BY-SA 2.5 (https://creativecommons.org/licenses/by-sa/2.5)], via Wikimedia Commons

Firstly, the data was pooled over forwarders, operators and stands, separately for unloaded driving, loading drive, and loaded driving speeds, and unloaded driving, loading drive, and loaded driving distances. Driving observations also include simultaneous crane work and driving, see Manner et al. (2016) for more details. Secondly, a possible association between the forwarder driving speed and distance driven was analysed for the three different work elements.

However, the data needed to be filtered before the analyses were conducted. This filtering was conducted in three stages. In the first stage, loads that came from uncommon or unordinary work were filtered out. This comprised e.g. forwarding logs during the construction of railways, motorways, and powerlines. In the second stage, loads that contained values that raised suspicion of measurement errors were filtered out. The following criteria were applied in stage two: unloaded and loaded distances should be more than 0 m·load^{-1}; productive machine (PM) time should be at least 10 min·load^{-1}; unloading distance should be below 500 m·load^{-1}; and loading drive distance should be at least 10 m·load^{-1}. In the third stage, loads in which individual observations deemed to have a too large impact on the analysis were filtered out. This filtering was based on 50% of the median driven distance (distance range), and 1% of the number of observations for each of the three work elements. This corresponded to a distance range of 99.7, 96.8, and 71.1 m for unloaded driving, loading drive, and loaded driving, respectively, and 45 observations for all three work elements. These values did not change as observations were removed. The observation with the longest forwarding distance for each work element was identified. This observation was then removed if it had fewer than 45 observations within the given distance range for that work element. This procedure was repeated until the observation with the longest distance for each work element had at least 45 other observations within the distance range. After all three filtering stages, the original number of loads (n = 8,868) was reduced to 4,392 loads for driving unloaded, 4,367 loads for loading drive, and 4,423 loads for driving loaded.

Data analysis

The data was further divided into 25 m distance classes (starting from 0 m) with the closed lower bound and open upper bound. The mean, median, standard deviation (SD), median absolute deviation (MAD), the 5th and 95th percentiles, minimum, and maximum were then calculated for the driving speed of each work element in these distance classes. Spearman's rank correlation coefficient (r_s) and Pearson's product-moment correlation coefficient (r_p) were used on this whole filtered dataset to assess associations between driven distances and driving speed. Least- squares regression analysis was used to further investigate the association between the respective driving speed and distance observations. In these regressions, unloaded driving, loading drive, and loaded driving speeds were the dependent vari-

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ables, and unloaded, loading and loaded distances driven were the respective independent variables. Adjusted coefficient of determination (*Adj* R^2) and regression coefficient were used to evaluate how well the regression functions fitted the data. Predicted coefficient of determination (*Prd* R^2) was used to evaluate the functions for over-fitting. When dependent variables had to be transformed, Snowdon (1991) ratio corrections were used to correct for the logarithmic bias when values were back-transformed. Regression functions with *Adj.* R^2 above 5% were considered relevant.

To investigate associations between driving speed percentiles and the distance driven, quantile regression was applied for the 5th, 15th, 85th and 95th percentiles (Koenker 2004). The Barrodale and Roberts algorithm was used in the quantile regression. The dependent variables of regressions were unloaded driving, loading drive and loaded driving speed, with unloaded driving, loading drive and loaded driving distance as the respective independent variables (Koenker, d'Orey 1987, 1994). These above-mentioned variables were also used in a quantile regression for the median (50th percentile) to investigate if extreme values had a large impact on the least-squares regression function.

All statistical calculations and tests were conducted in R (Core Team R 2015) using Rstudio (Version 0.99.896, 2015) (R Studio Team 2015).

RESULTS

Unloaded

The average unloaded driving speed in the filtered data was 3.29 km·h^{-1} (SD = 1.04), while the mean unloaded distance driven was 240 m (SD = 199). The median unloaded driven speed was 3.26 km·h^{-1} (MAD = 0.87), while the median driving unloaded distance was 194 m (MAD = 185). The r_p and r_s were 0.504 and 0.579, respectively (P < 0.0001). The descriptive values for the distance categories revealed a tendency that average driving speed increased with increasing driving distance (Table 1).

The least-squares regression analysis indicated a relatively clear logarithmic association between unloaded distance driven and driving speed (Table 2, Fig. 2). The least-squares regression, and the quantile regression of the 95th, 85th, 50th (median), 15th and 5th percentiles increased logarithmically with distance until about 200 m (Table 3, Fig. 2). Thereafter, the models started to plateau. The logarithmical increase was quite similar for the quantile regression median and the 15th and 5th percentiles, while the 95th and 85th percentiles had a relatively slower increase. The variation in the data decreased with increasing distance driven, and this variation was asymmetric but it became more symmetric with increased distance.

Loading

The average loading drive speed in the filtered data was 1.94 km·h^{-1} (SD = 0.47), while the mean loading distance driven was 213 m (SD = 134). The median loading drive speed was 1.90 km·h^{-1} (MAD = 0.47), while the median loading distance driven was 191 m (MAD = 127). The r_p and r_s were 0.214 and 0.159, respectively (P < 0.0001). The descriptive values for the distance categories revealed a tendency that average driving speed increased with increasing driving distance (Table 4).

There was a very weak quadratic association between loading drive speed and driving distance in the least-squares regression function (Table 2, Fig. 2). The least-squares regression, and the quantile regression of the 95th, 85th, 50th (median), 15th and 5th percentiles, were relatively flat during roughly half of the studied distance and then showed a slow increase (Table 3, Fig. 2). These regressions indicated that the increase was faster for the higher percentiles and relatively small for the 5th percentile. This situation meant that the variation was asymmetric but constant for about half the studied distance, and then became increasingly asymmetric with increasing distance.

Loaded

The average driving loaded speed in the filtered data was 2.74 km·h^{-1} (SD = 0.80), while the mean driving loaded distance was 189 m (SD = 167). The median driving loaded speed was 2.66 km·h^{-1} (MAD = 0.67), while the median driving loaded distance was 138 m (MAD = 139). The r_p and r_s were 0.234 and 0.297, respectively (P < 0.0001). The descriptive values for the distance categories revealed a tendency that average driving speed increased with increasing driving distance (Table 5).

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Table 1. Descriptive statistics for the driving unloaded speed based on distance intervals

Driving distance (m)*	*n*	Mean distance (m)	Driving unloaded speed (km·h^{-1})							
			mean	SD	median	MAD	5th percentile	95th percentile	min	max
0–25	528	9	1.89	0.73	1.81	0.62	0.86	3.06	0.00	5.46
25–50	238	38	2.65	0.92	2.51	0.76	1.49	4.51	0.76	6.46
50–75	221	62	2.89	0.78	2.79	0.63	1.86	4.26	1.31	6.08
75–100	221	88	3.10	0.76	3.00	0.59	1.98	4.57	1.55	6.24
100–125	315	112	3.22	0.80	3.07	0.67	2.14	4.67	1.44	6.03
125–150	291	138	3.32	0.86	3.20	0.74	2.18	5.15	1.70	6.10
150–175	222	162	3.43	0.79	3.31	0.67	2.44	4.84	1.65	6.63
175–200	208	188	3.38	0.69	3.30	0.59	2.43	4.66	1.18	5.50
200–225	206	212	3.49	0.79	3.37	0.66	2.43	4.95	1.63	7.19
225–250	183	238	3.57	0.83	3.48	0.67	2.49	4.65	1.85	9.71
250–275	189	262	3.58	0.64	3.49	0.61	2.64	4.68	2.29	6.57
275–300	184	287	3.62	0.72	3.54	0.62	2.62	4.97	2.25	6.35
300–325	165	311	3.66	0.72	3.53	0.65	2.66	4.96	2.23	6.26
325–350	145	338	3.62	0.73	3.58	0.61	2.51	4.75	2.31	7.44
350–375	136	363	3.73	0.84	3.66	0.60	2.63	4.89	1.83	8.36
375–400	119	388	3.62	0.71	3.52	0.60	2.69	4.70	1.88	6.53
400–425	95	412	3.51	0.66	3.51	0.61	2.62	4.61	1.81	5.46
425–450	80	437	3.85	0.75	3.77	0.77	2.82	5.07	2.28	6.10
450–475	71	460	3.90	1.06	3.71	0.88	2.77	5.44	2.12	9.05
475–500	70	487	4.21	1.06	4.10	1.21	2.20	5.79	2.06	7.16
500–525	54	513	3.87	0.77	3.67	0.55	3.03	5.20	2.38	6.66
525–550	47	537	3.91	0.72	3.68	0.55	2.89	5.22	2.60	5.81
550–575	48	561	4.12	1.08	3.76	0.60	3.11	5.72	3.00	9.35
575–600	50	588	4.06	0.90	3.83	0.93	2.80	5.56	2.70	6.50
600–625	46	610	3.79	0.81	3.76	0.73	2.85	5.04	1.95	6.36
625–650	43	638	4.30	1.30	3.95	0.82	2.96	6.22	2.77	9.48
650–675	29	664	4.13	1.52	3.57	1.21	2.53	5.74	2.52	9.85
675–700	27	686	4.06	0.97	4.02	0.86	2.76	5.63	2.49	6.81
700–725	25	713	3.99	0.75	3.98	0.71	3.02	5.14	2.97	6.02
725–750	31	740	4.54	1.89	4.20	0.76	3.04	7.36	2.54	12.77
750–775	21	763	4.01	1.13	3.84	0.92	2.84	5.54	2.65	7.78
775–800	21	788	3.51	0.69	3.27	0.60	2.81	4.29	2.70	5.62
800–825	11	811	4.67	1.33	4.39	1.42	3.01	6.73	2.74	7.08
825–850	23	836	4.77	1.88	4.12	0.63	3.32	9.52	2.57	10.13
850–875	8	862	4.02	0.69	4.11	0.57	3.02	4.80	2.86	4.93
875–900	11	886	4.37	1.04	3.83	0.45	3.53	6.26	3.53	6.26
900–925	7	910	4.20	0.93	4.44	0.62	2.90	5.14	2.89	5.25
925–950	3	927	3.52	0.44	3.43	0.43	3.17	3.94	3.14	4.00

*Distance from closed lower bound to open upper bound, *n* – observations in category, SD – standard deviation, MAD – median absolute deviation

There was a weak logarithmic association between driving loaded speed and driving distance in the least-squares regression function (Table 2, Fig. 2). The least-squares regression, and the quantile regression of the 95th, 85th and 50th (median) percentiles, increased at the beginning and then flattened out, while the 5th and

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Table 2. Least-squares regression functions for the association between driving distance (m) and driving speed (km·h^{-1}) for unloaded, loading, and loaded work

Driving work element	Dependent variable	Correction	Range (m)	Parameter			Model´s			
				Variable	Coefficient	Standard error	RMSE	*Adj R*^{2} (%)	*Prd R*^{2} (%)	df
Unloaded	LN (Speed)	0.9744	1–928	Intercept LN (Distance)	1.8700×10^{-1} 1.9270×10^{-1}	0.1444×10^{-1} 0.0283×10^{-1}	0.2637	51.41	51.20	4,390
Loading	Speed	–	11–731	Intercept Distance^2	1.8526×10^{-0} 1.3498×10^{-6}	0.0089×10^{-0} 0.0873×10^{-6}	0.4600	5.17	5.08	4,365
Loaded	LN (Speed)	0.9866	1–761	Intercept 1/√ Distance	1.0949×10^{-0} -1.1156×10^{-0}	0.0057×10^{-0} 0.0335×10^{-0}	0.2752	20.07	19.71	4,421

LN – natural logarithm, RMSE – root mean square error, *Adj R*^{2} – adjusted coefficient of determination; *Prd R*^{2} – predicted coefficient of determination, df – degrees of freedom, all values of parameters and models were $P < 0.0001$

15th percentiles increased continually (Table 3, Fig. 2). These values indicate that the mean, median, and the 85th and 95th percentiles had relatively constant values for driving loaded speed at most driving distances, while percentiles below the mean increased. This situation indicated an asymmetric variation that increased with driving distance.

DISCUSSION

The association between driving speed and driving distance was strongest for driving unloaded while it was weaker for loading drive and driving loaded (Tables 4 and 5, Fig. 2). This association could be both because of driving distance acting as an indirect factor as well as a direct factor. The driving distance could be an indirect factor that leads to improved planning and strip road conditions as well as more time spent on haul roads of better quality. At the same time driving distance is a proxy for these direct factors that are difficult to measure. Possible effects of driving distance as a direct factor are decreased impacts of accelerations and decelerations (which theoretically should have an impact on driving speed), and operators' mental stress to compensate longer driving distances with higher speed.

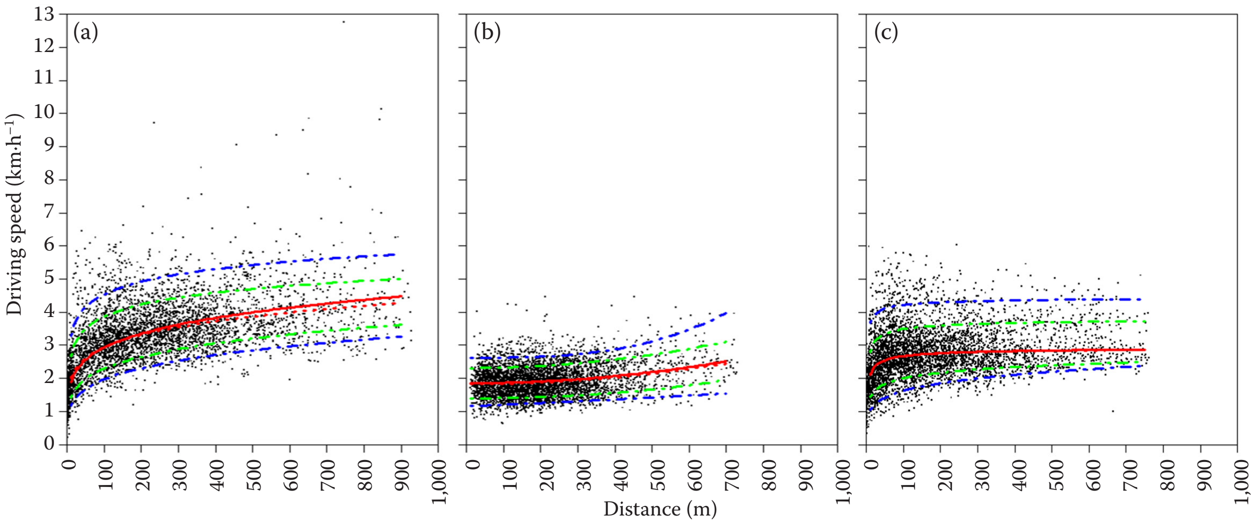

Fig. 2. Observed driving speed in dependence on driving distance when forwarding in central Sweden: (a) driving unloaded speed, (b) loading drive speed, (c) driving loaded speed. Estimated least-squares regression functions (red solid line) and quantile regression for the 50th (median; red dashed line), 95th (blue line), 85th (green line), 15th (green line) and 5th (blue line) percentile for the association between driving speed and distance

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Table 3. Quantile regression functions for the 5th, 15th, 50th (median), 85th, and 95th percentiles for the unloaded, loading and loaded driving speed (km·h^{-1}) based on unloaded, loading and loaded driving distance (m), respectively,

Driving work element	Percentile	Dependent variable	Intercept		Variable	Independent variable	
			Coefficient*	SE		Coefficient*	SE
Unloaded	5th	LN (Speed)	–0.37807	0.04202	LN (Distance)	2.2914×10^{-1}	0.0771×10^{-1}
	15th	LN (Speed)	–0.12170	0.02899	LN (Distance)	2.0687×10^{-1}	0.0530×10^{-1}
	50th	LN (Speed)	0.30298	0.01751	LN (Distance)	1.6889×10^{-1}	0.0327×10^{-1}
	85th	Speed	1.47958	0.01720	LN (Distance)	5.1864×10^{-1}	0.0299×10^{-1}
	95th	Speed	2.01071	0.22546	LN (Distance)	5.4948×10^{-1}	0.4126×10^{-1}
Loading	5th	LN (Speed)	0.14195	0.01424	Distance	4.1747×10^{-4}	4.5558×10^{-5}
	15th	LN (Speed)	0.33444	0.00774	Distance^2	6.8716×10^{-7}	7.4038×10^{-8}
	50th	Speed	1.82353	0.01162	Distance^2	1.2773×10^{-6}	1.1862×10^{-7}
	85th	Speed	2.30858	0.01319	Distance^2	1.6261×10^{-6}	2.0912×10^{-7}
	95th	Speed	2.62392	0.02018	Distance^3	3.9477×10^{-9}	2.5084×10^{-10}
Loaded	5th	LN (Speed)	–0.38443	0.05453	LN (Distance)	1.8875×10^{-1}	0.1011×10^{-1}
	15th	Speed	0.86344	0.04943	LN (Distance)	2.4666×10^{-1}	0.0986×10^{-1}
	50th	LN (Speed)	1.09048	0.00805	1/√ Distance	-1.0942×10^{-0}	0.0640×10^{-0}
	85th	LN (Speed)	1.35338	0.01159	1/√ Distance	-1.0312×10^{-0}	0.0953×10^{-0}
	95th	LN (Speed)	1.50469	0.01795	1/√ Distance	-6.5420×10^{-1}	1.8500×10^{-1}

LN – natural logarithm, SE – standard error, *indicates values $P < 0.0001$

The use of quantile regression seemed to work well on the data and enabled a better investigation of the variation in driving speed than what the use of only least-squares regression and descriptive analysis of categories enables. Quantile regression was particularly useful for the unloaded and loaded driving speeds because their response variable was transformed (meaning that the normal confidence interval would be difficult to use after retransformation). Transformed response variables are not a concern for quantile regression (Cade, Noon 2003). Quantile regression also allowed the percentiles to be modelled with different independent variables than what least-squares regression functions require, and this ability is an advantage when dealing with asymmetrically varying data. Many of the differences revealed in our study would have been difficult to detect statistically by more traditional methods used in forest technology.

Kumazawa et al. (2011) suggested that stress on long distances could lead to higher driving speed. Since stress can affect driving behaviour in road traffic (af Wåhlberg 1997; Matthews et al. 1998; Stradling 2007), is it quite likely to play a role in forwarding as well. It is therefore likely that at least part of the association between driving speed and distance can be explained by operator's stress.

Driving unloaded speed for a specific forwarder model should be influenced only by the ground conditions (bearing capacity, roughness, and slope) and physical obstacles, while loading drive and driving loaded speed should be affected also by other factors like load size and number of load stops (Tufts 1997; Akay et al. 2004; Nurminen et al. 2006). These details probably explain dissimilarity in the association between driving speed and work elements.

Loading drive speed required long driving distances to show any association with distance. High percentiles had a faster increase in loading drive speed than low percentiles (the 5th percentile was close to flat, Fig. 2b). This difference can be explained by the fact that loading drive speed (in addition to ground conditions) is also affected by the number of loading stops and the distance between loading stops (Gullberg 1997; Tufts 1997). The number of loading stops depends on the log concentration of forwarded assortments, so a longer distance is needed before the association between driving speed and the loading drive work element can be detected.

Driving loaded speed increased to some extent with increasing distance and then flattened out (Fig. 2c). The lower percentiles increased more than the high percentiles, leading to a decreased variation in speed

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Table 4. Descriptive statistics for the loading drive speed based on distance intervals

Driving distance (m)*	n	Mean distance (m)	Loading drive speed (km·h^{-1})							
			mean	SD	median	MAD	5th percentile	95th percentile	min	max
10–25	53	20	1.69	0.44	1.67	0.38	0.97	2.32	0.80	3.25
25–50	255	39	1.87	0.45	1.84	0.44	1.20	2.60	0.78	4.02
50–75	323	63	1.90	0.41	1.93	0.43	1.25	2.56	0.74	3.03
75–100	312	88	1.88	0.46	1.86	0.46	1.22	2.76	0.62	3.21
100–125	349	113	1.87	0.44	1.82	0.43	1.24	2.66	0.83	4.24
125–150	336	138	1.87	0.47	1.84	0.48	1.19	2.64	0.92	4.21
150–175	340	162	1.87	0.47	1.81	0.44	1.17	2.75	0.86	4.04
175–200	358	188	1.89	0.44	1.85	0.48	1.25	2.65	0.94	3.14
200–225	298	212	1.89	0.48	1.82	0.46	1.26	2.66	0.95	4.45
225–250	312	237	1.95	0.42	1.94	0.41	1.27	2.65	1.07	3.43
250–275	244	262	1.99	0.42	1.98	0.47	1.33	2.67	1.13	3.31
275–300	229	288	1.96	0.42	1.92	0.41	1.33	2.68	1.02	3.23
300–325	191	312	1.94	0.48	1.87	0.52	1.29	2.79	0.95	3.19
325–350	144	337	1.96	0.44	1.94	0.47	1.31	2.73	1.10	3.24
350–375	131	361	2.05	0.50	2.00	0.58	1.37	2.87	1.16	3.55
375–400	87	387	2.16	0.48	2.21	0.47	1.51	2.81	1.29	4.18
400–425	82	412	2.02	0.49	1.97	0.57	1.35	2.83	1.11	3.42
425–450	51	437	2.08	0.51	2.03	0.49	1.32	2.87	1.03	3.73
450–475	60	462	2.17	0.56	2.04	0.54	1.47	3.09	1.25	4.46
475–500	38	485	2.21	0.58	2.17	0.54	1.47	3.23	1.20	3.81
500–525	33	513	2.18	0.51	2.19	0.56	1.43	3.07	1.24	3.40
525–550	22	538	2.18	0.44	2.13	0.49	1.47	2.84	1.36	3.07
550–575	28	562	2.41	0.64	2.41	0.54	1.57	3.48	1.19	4.14
575–600	22	586	2.18	0.58	2.27	0.56	1.30	2.72	1.25	3.80
600–625	13	612	2.27	0.76	2.19	0.63	1.36	3.52	1.16	3.90
625–650	20	639	2.63	0.59	2.71	0.59	1.80	3.58	1.65	3.66
650–675	12	662	2.38	0.65	2.40	0.31	1.47	3.33	1.37	3.95
675–700	9	686	2.39	0.66	2.26	0.50	1.80	3.42	1.75	3.89
700–725	12	713	2.60	0.53	2.42	0.20	2.13	3.52	2.09	3.96
725–750	3	728	2.25	0.18	2.17	0.06	2.13	2.43	2.13	2.46

*Distance from closed lower bound to open upper bound, n – observations in category, SD – standard deviation, MAD – median absolute deviation

at longer distances. Driving loaded speed should be affected (in addition to ground conditions) by load size which varies between loads (Tufts 1997). The variation in load size should be larger at short distances than at long distances because small loads at long distances are inadvisable (from a productivity point of view). These details should explain the association between driving loaded speed and distance.

We investigated the 5th, 15th, 85th and 95th percentiles instead of only the usual 5th and 95th percentiles. This decision was made because Cade and Noon (2003) recommended using more than two percentile classes as the values of the coefficients in the quantile regression can change quickly. These investigated percentile classes differed from the classes previously used by Lu et al. (2017) on simulated forest machine data. However, their application of quantile regression was quite different from ours since they focused on tree characteristics while we focused on machine performance.

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Table 5. Descriptive statistics for the driving loaded speed based on distance intervals

Driving distance (m)*	n	Mean distance (m)	Driving loaded speed (km·h^{-1})							
			mean	SD	median	MAD	5th percentile	95th percentile	min	max
0–25	466	12	2.03	0.79	1.92	0.69	0.95	3.50	0.31	5.98
25–50	472	38	2.54	0.80	2.45	0.73	1.38	3.99	0.88	5.94
50–75	440	63	2.73	0.80	2.64	0.69	1.58	4.22	0.85	5.63
75–100	329	87	2.87	0.87	2.69	0.66	1.61	4.57	1.11	5.80
100–125	339	112	2.77	0.72	2.70	0.61	1.76	4.03	1.03	5.75
125–150	303	138	2.78	0.77	2.71	0.67	1.68	4.41	1.10	5.53
150–175	226	162	2.82	0.76	2.76	0.65	1.77	4.42	1.19	5.70
175–200	211	188	2.96	0.74	2.83	0.64	2.00	4.35	1.34	5.09
200–225	196	212	2.85	0.66	2.74	0.58	2.00	4.22	1.71	5.46
225–250	188	236	2.86	0.70	2.75	0.55	1.89	4.27	1.41	6.04
250–275	179	263	2.94	0.68	2.84	0.65	1.96	4.23	1.68	5.25
275–300	139	287	2.87	0.69	2.77	0.75	1.91	4.06	1.62	4.88
300–325	111	312	2.81	0.65	2.63	0.57	1.92	4.21	1.48	4.65
325–350	128	337	2.82	0.67	2.77	0.67	1.86	4.00	1.49	4.93
350–375	94	363	2.81	0.62	2.67	0.43	2.02	4.01	1.79	5.27
375–400	62	389	2.93	0.62	2.82	0.70	2.11	3.79	1.98	5.26
400–425	62	411	2.89	0.68	2.76	0.57	2.03	4.03	1.84	5.09
425–450	69	437	2.88	0.77	2.67	0.51	2.07	4.35	1.81	5.45
450–475	54	462	3.02	0.62	2.86	0.68	2.27	4.02	2.00	4.66
475–500	40	488	3.04	0.71	2.81	0.67	2.25	4.17	2.22	4.67
500–525	45	513	3.00	0.62	2.91	0.67	2.30	4.06	2.13	5.01
525–550	43	537	2.94	0.63	2.79	0.56	2.29	4.24	1.98	4.78
550–575	37	562	3.26	0.72	3.12	0.75	2.25	4.62	2.20	4.86
575–600	34	586	3.15	0.66	3.03	0.65	2.28	4.30	1.96	4.66
600–625	41	613	3.22	0.60	3.08	0.66	2.53	4.22	2.41	4.50
625–650	28	635	3.22	0.80	2.97	0.71	2.25	4.61	2.10	5.00
650–675	23	663	2.97	0.67	2.90	0.45	2.44	3.93	1.00	4.39
675–700	23	685	3.16	0.71	2.89	0.58	2.43	4.43	2.36	4.88
700–725	12	708	2.92	0.44	2.81	0.30	2.53	3.78	2.49	3.81
725–750	21	739	2.92	0.69	2.71	0.40	2.20	3.94	2.14	5.11
750–775	8	756	3.00	0.60	2.67	0.25	2.48	3.87	2.44	3.98

*Distance from closed lower bound to open upper bound, n – number of observations in category, SD – standard deviation, MAD – median absolute deviation

Comparison with previous studies

Some previous studies found an association between driving speed and distance at the load level, but they could not quantify it (Nurminen et al. 2006; Ghaffarian et al 2007; Kumazawa et al. 2011). We have however quantified the association between forwarder driving speed and distance at the load level, just like Väkevä et al. (2001) previously did at the stand level. Our results are valid for larger forwarders in stands of central Sweden. Nevertheless, it is still interesting to compare our results with those of previous studies. Compared to Väkevä et al. (2001), our observed least-squares regression model for driving unloaded speed was basically the same

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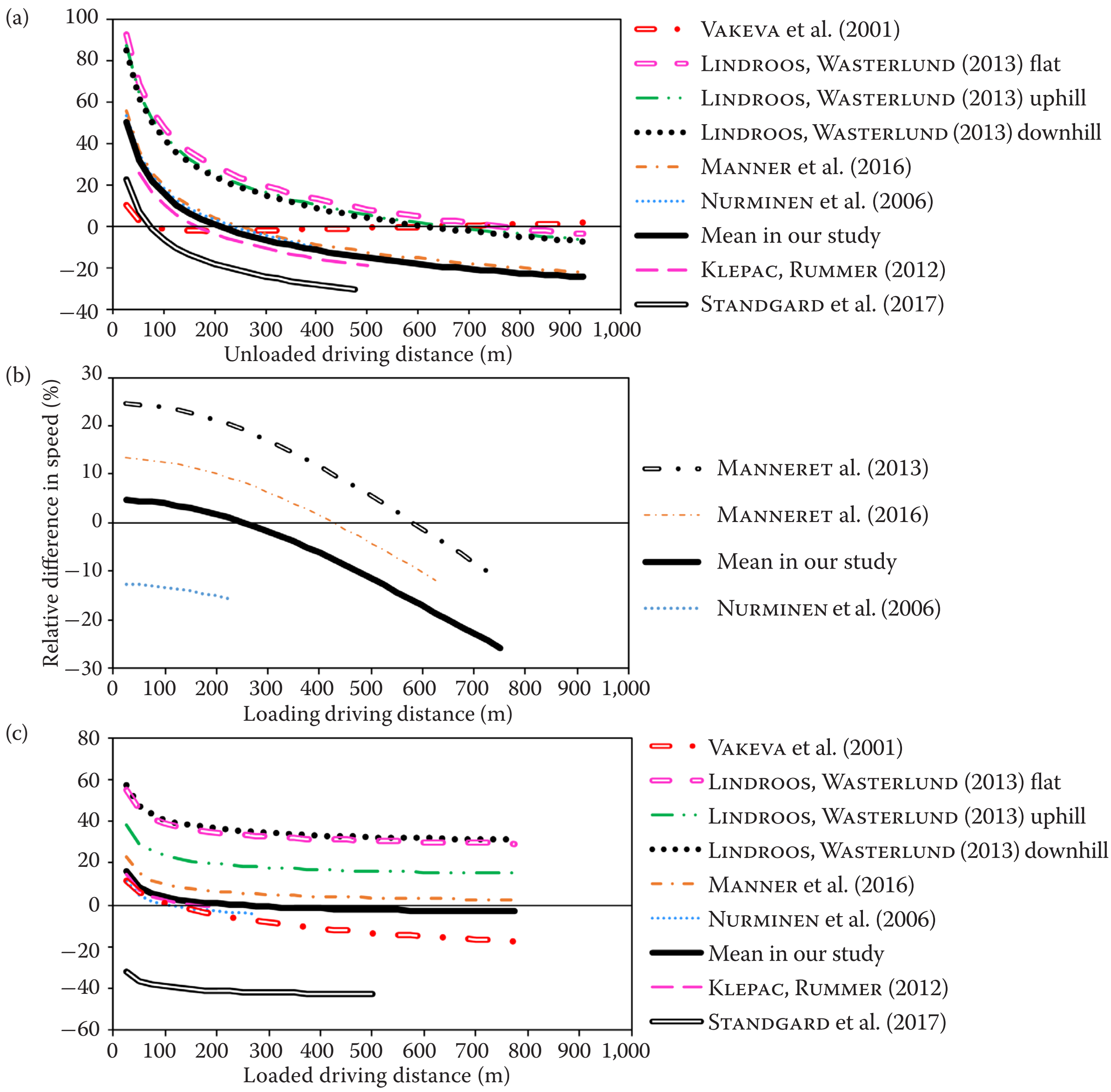

Fig 3. The relative difference (%) in unloaded driving (a), loading drive (b) and loaded driving speed (c) between the least-squares regression functions from our study, the mean in our study, and the observed values reported in the following publications: Strandgard et al. (2017) for a forwarder with an 18-ton maximum load size; Manner et al. (2016) for forwarders with a 19- ton maximum load size; Lindroos and Wästerlund (2013) for a forwarder with 15.1-ton maximum load size; Manner et al. (2013) for a forwarder with 14-ton maximum load size; Klepac and Rummer (2012) for a forwarder with maximum 20-ton load size; and Nurminen et al. (2006) for forwarders with an 11–14 ton maximum load size

(–2 to 2% difference) at all distances > 50 m (Fig. 3a). However, there was a larger difference in the driving loaded speed, since Väkevä et al.'s (2001) results gave 3–11% faster speed at distances of 0–75 m, and 4–18% lower speeds at 175–775 m than our results (Fig. 3c).

Differences between fixed speeds and speeds estimated according to driving distance can be quite large. Our least-squares regression function and the mean from our study mostly estimated approximately the same driving loaded speed (except at short distances where it could be up to 16% above the regression function estimate; Fig. 3c). However, the difference was much larger for the unloaded and loading driving speeds, +51 to –25% and +5 to –26%, respectively. Naturally, the difference was even larger when comparing with the fixed speed reported in other studies.

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These differences are large enough that using fixed speed could negatively affect the accuracy of calculations when terrain conditions are not assumed or distances deviate substantially (from those reported in the studies). However, if the investigated situation is very similar to that of a study with fixed driving speed, it is probably more suitable to use a fixed speed. Also, if specific terrain conditions are used, it is probably best to use the results from other studies.

Weaknesses

Observations with short driving distances clearly dominated all three work elements. This situation was the cause for the filtering. There was, of course, an unfortunate loss of information when observations without obvious measurement errors were removed. Nevertheless, this filtering was deemed necessary as otherwise a handful of observations on long driving distances would have had an very significant impact on both the least-squares and quantile regressions. And because of the potential problems with errors in the data, we chose to investigate the 5th, 15th, 85th, and 95th percentiles, since it is likely that errors are more prevalent at extremely high or low driving speeds.

There are many variables that were not accounted for in our data material, and in some cases distance is confounded with other variables that influence the driving speed (Nurminen et al. 2006; Ghaffarian et al 2007). In other words, speed is often a proxy for other variables that are not measured or are difficult to measure, such as better planning and more time spent on high-quality haul roads. Meanwhile, there are also factors that are more directly affected by distance, such as operator's stress and the number of decelerations. In our study, we could not distinguish between these direct and indirect factors, but future studies might do so.

Recommendations

When designing future studies of forwarding, our results can be of interest because they indicate that travelling distance (in addition to the other commonly investigated variables like ground condition, slope, load size, etc.) can explain some of the variations in driving speed. Also, our results can be of interest when simulating forwarder work and when optimizing forwarding routes, especially when there is limited information about the other variables that affect forwarding productivity (quantile regressions can also be especially interesting in this situation).

CONCLUSIONS

Based on our large data set from stands located in central Sweden, there seems to be a fairly strong connection between speed and driving distance during forwarding work. Granted, driving distance is probably mostly a proxy for other variables that affect speed, but driving distance is also a direct factor to some extent because of its effect on operator's stress and relative machine acceleration and deceleration time. Thus, we recommend researchers and managers to consider including distance as an explanatory variable when modelling forwarding in future studies. Correspondingly, when only distance is used in system analyses and similar modelling of forwarding work, it is probably better to rather use distance-dependent variable speeds than constant speeds. Also, our study shows that quantile regression is a useful tool also for forest technology/forest operations researchers.

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